10/579213
IAP9 Rec'd PCT/PTO 12 MAY 2006

Automated credit risk indexing system and method

The present invention relates to a computer-aided system and such a method for automated credit risk indexing, the system comprising at least means for acquiring and evaluating company balance data and/or stock market data, in which evaluation expected values for crediting data of individual companies are calculated. In particular, the present invention relates to a method and to a system for the automatic management of credit portfolios, taking into consideration default correlation effects and individual credit risks. The invention also relates to a computer program product for carrying out this method.

For many questions posed as part of the evaluation of financial titles with a credit risk and of the estimation of risk determinations for individual credits and/or credit portfolios, it is today necessary to take into consideration correlation effects of company balance data and stock market data, on the one hand, but also of the credit risks and of the default risks with respect to one another. In the prior art, there are the most varied methods for determining credit risks and credit risk correlations which provide for quantification. However, since the questions posed are based on dynamic and extremely nonlinear effects, all these concepts have been beyond any automation of the process until today. This is clearly shown in the prior art in that, in particular, these processes have to be geared to an empirical estimation of the correlation-determining parameters. Although it is known in the prior art that individual credit risks can be calculated not only on the basis of company balance data but that, e.g., stock market data also supply relevant information for the credit risks, these parameters will mostly only be taken into consideration

partially or not at all in the processes of the prior art because of the complexity of the relationships. The fundamental truth known from stock analysis, that the portfolio risk is not identical with the sum of the individual risks, similarly applies to portfolios of credit risks. Whereas the explicit measurement of portfolio risks and their optimization as part of share investments belongs to the standard routines in asset management today, the consideration of portfolio effects as part of a credit risk measurement is scarcely covered in the prior art. However, a comprehensive quantification of individual risks and portfolio effects is extremely important technically for an investing company and/or a bank for various reasons. It is only the quantification of individual risks and of portfolio effects that allows a quantification of the overall risk in the credit field and thus an estimation of the economically adequate support with own capital. The quantification also allows a portfolio control of the credit portfolio which explicitly takes into consideration the marginal contribution of individual positions (credit risks) to the overall risk. When asset backed securities are documented, a limited default risk frequently remains with the issuer (e.g. the first two percent of the defaults of the documented pool are borne by the issuer). The evaluation of such a default guarantee requires the determination of the probability of a default of x% of the parties receiving credit for various values of x. This problem is formally identical with the determination of the value at risk of a portfolio. The only difference lies in the use of different quantiles of the frequency distribution. Furthermore, the evaluation of credit derivatives, taking into consideration the default risk of the contracting party, also requires a quantification of the credit risks or, respectively, of correlation effects in the credit field. E.g., the value of a

default swap obviously depends on a probability with which both the basic party taking the credit and the other party of the swap will jointly drop out. In the case where credit derivatives are concluded for baskets of different debtors, a basket default swap, in particular, can lead, e.g. to a default payment if at least one of a number of debtors drops out during the term. Calculating the probability of the default payment and thus the evaluation of the swap requires the correlation of default events. From all these problems, a comprehensive quantification of individual risks and portfolio effects is extremely important technically for an investing company and/or a bank. However, an automated comprehensive quantification of individual risks and credit portfolio risks is not possible in any way with the necessary reliability of the numbers obtained using the methods of the prior art until today.

The credit risk methods described in the prior art can be roughly divided into two categories. All methods comprise both individual credit risks and default correlations. The two categories are so-called "asset value" methods and methods "based on default rates". The asset value methods are attributable to Merton (1974) who describes credits as put options and evaluates them with the Black/Scholes calculation. In these approaches, underlying is the value of the assets of the credit-taking company for the value development of which a geometric Brownian movement is usually assumed:

$$dV_A = \mu_A V_A dt + \sigma_A V_A dz$$

where μ_A is assumed to be the expected return, σ_A as volatility of the assets and dz represents the

increment of a Brownian movement. The default occurs when the value of the assets is less than the due credit repayment (or a differently defined default barrier). Accordingly, the magnitude of the default correlation significantly depends on the magnitude of the correlation of the asset returns in this method. To map correlations between two parties receiving credit, a common value development of the assets must be specified. I.e. a return correlation ρA of the two stochastic processes dV_A^1 and dV_A^2 must be specified. The default correlation is not yet determined with the choice of return correlation since the default correlation depends on the definition of the default barrier. However, the asset value models differ in the definition of the default barrier so that an identical return correlation can lead to different default correlations. One of the problems of the prior art follows from the fact that the approaches which only allow the possible default at an exogenously defined time (Merton, CreditMetrics and KMV) imply identical default correlations with corresponding choice of input parameters whereas models in which the default can be triggered at any time in an observation interval (Black/Cox, Longstaff/Schwarz) generate different default correlations from these. Another disadvantage, especially of the Merton approach, is that default is only possible at a time T. Various methods of the prior art (e.g. Black/Cox or Longstaff/Schwarz) attempt to circumvent this problem by means of a corresponding modification of the asset value method. In this modified method, a default occurs if the asset value falls below the default barrier. These further developments of the "first passage time" method assume a stochastic default barrier and are based on deviating assumptions about the (stochastic) risk-free interest, its correlation with other quantities and the recovery rate (E. Briys and F. de Varenne, 1997, Valuing Risky

Fixed Rate Debt: An Extension, Journal of Financial and Quantitative Analysis 32, 239-248). Although it can be shown (e.g. C. Zhou, 1997, Default Correlation: And Analytical Result, Working Paper) that, e.g., the default correlation for methods based on a time-dependent non-stochastic default barrier can be analytically determined, one of the main disadvantages of these methods is that they cannot manage without model assumptions with respect to distributions (e.g. normal distribution, Poisson distribution, binomial distribution etc.) and, therefore, are never free of distribution. Similarly, it is not possible to manage without an empirical estimation of correlation-determining parameters even in these methods which, in principle, does not lend itself to an automation of the method.

In the second category of methods of the prior art, the methods "based on default rates", the process of credit defaults is directly modeled instead of defining a stochastic process for company values which indirectly causes the defaults. In these methods, it is only specified how high the probability for the occurrence of a default in each discrete time interval is. As examples, the methods for evaluating financial instruments with credit risks by Jarrow/Turnbull, Jarrow/Lando/Turnbull, Duffie/Singleton and Madan/Unal can here be mentioned in which the default is described as a first jump into a Poisson process (also called jump process). As a stochastic process, a Poisson process consists of paths which have a change, a jump, only at a few discrete points. The following applies to the counting function N of a Poisson process:

$$P(\Delta N_t = 1) \approx \lambda(t, X)\Delta t$$

$$P(\Delta N_t = 0) \approx 1 - \lambda(t, X)\Delta t$$

λ designates the intensity of the Poisson process which can depend on the time or other exogenous variables. In some models, the intensity λ is not defined as a deterministic function but as a stochastic process which, in turn, is partially driven by stochastic factors (e.g. interest, share prices or ratings). A representation of these Cox processes can be found in, e.g., S. Lando, 1998, On Cox Processes and Credit Risky Securities, Working Paper. Let X be a d-dimensional stochastic process which describes the possible (correlated) development paths of d factors. Let $\lambda: R^d \rightarrow R$ be a function which can be interpreted as the marginal default probability in dependence on the d factors, then $\lambda(X_t)$ is a time-dependent stochastic intensity. If then a time interval [O,T] is considered, then for each path of the factors $\lambda(X_t)_{0 \le t \le T}$ the probability is calculated that no default will occur, that is to say $N_T = 0$, as

$$P(N_T = 0 \mid (X_t)_{0 \le t \le T}) = e^{-\int_0^T \lambda(X_t)dt}$$

For a firmly selected path of the factors, $\lambda(X_t)$ is a deterministic, time-dependent function, so that

$$e^{-\int_0^T \lambda(X_t)dt}$$

calculates the survival probability with respect to the path considered. If then the entire distribution of the

factors X is considered, a default probability is obtained for each point of the factor distribution, that is to say, overall, a distribution of ex-ante stochastic default probabilities over the period considered.

If the default is modeled with the aid of a Poisson process as described above, correlations between default events in these methods can be created in different ways: (i) for both parties receiving credit or a number of parties receiving credit, identical jump processes are assumed. In this approach, the debtors always drop out at the same time which represents an assumption which is meaningless for the modeling of credit risks; (ii) the intensity (marginal default probability) $\lambda(X_t)$ for two parties receiving credit is selected identically but the jump events are stochastically independent of one another. This method can be applied both to the case where the intensity is described by a deterministic function and to the case of stochastic intensities; (iii) the intensity $\lambda(X_t)$ is modeled as a stochastic process in that a stochastic process is used for X_t. If the intensities of two parties receiving credit each λ_1, λ_2 depend at least partially on the same elements of the vector of the state variables X_t, the default probabilities of the parties receiving credit are correlated. The default rates of different parties receiving credit are then not identical but they have a correlation structure which can map the empirically observed synchronism of the development of the default rates. In these methods, the arbitrage-free valuation approaches by Jarrow/Turnbull, Jarrow/Lando/Turnbull, Duffie/Singleton and Madan/Unal based on Poisson processes, in particular, can be used for evaluation of a credit portfolio and for determining the value at risk. In practice, these methods of the prior art have hardly been used until today. The great disadvantage of

these methods lies in their high degree of complexity and the large data requirements for an empirical calibration of the methods. These disadvantages have been preventing their use in banks or other creditors or generally in practice until today. As in the methods of the first category described above, it is not possible to get by without an empirical estimation of correlation-determining parameters in these methods which additionally makes it difficult or impossible to automate the method.

In principle, neural networks are known in the prior art and are used, e.g. for solving optimization tasks, pattern recognition, in artificial intelligence etc. Corresponding to biological nerve networks, a neural network consists of a multiplicity of network nodes, so-called neurons, which are connected to one another via weighted connections (synapses). The neurons are organized in network layers and interconnected. The individual neurons are activated in dependence on their input signals and generate a corresponding output signal. The activation of a neuron takes place via an individual weight factor by summation over the input signals. Such neural networks are capable of learning by systematically changing the weight factors in dependence on predetermined exemplary input and output values until the neural network shows a desired behavior within a defined predictable range of errors like, e.g. the prediction of output values for future input values. Neural networks thus have adaptive capabilities for learning and storing knowledge and associative capabilities for comparing new information with stored knowledge. The neurons (network nodes) can assume a state of rest or a state of excitation. Each neuron has a number of inputs and exactly one output which is connected to inputs of other neurons of the next network layer following or represents a corresponding output value in the case of an output

node. A neuron changes into the excitation state if a sufficient number of the inputs of the neuron are excited above a certain threshold value of the neuron, i.e. if the summation over the inputs reaches a certain threshold value. The knowledge is stored by adaptation in the weights of the inputs of a neuron and in the threshold value of the neuron. The weights of a neural network are trained by means of a learning process (see, e.g., G. Cybenko, "Approximation by Superpositions of a sigmoidal function", Math. Control, Sig. Syst., 2, 1989, pp. 303-314; M.T. Hagan, M.B. Menjaj, "Training Feedforward Networks with the Marquardt Algorithm", IEEE Transactions on Neural Networks, Vol. 5, No. 6, pp. 989-993, November 1994; K. Hornik, M. Stinchcombe, H. White, "Multilayer Feedforward Networks are universal Approximators", Neural Networks, 2, 1989, pp. 359-366 etc.).

It is an object of the present invention to demonstrate a new system and method for determining credit indices of individual credit risks and credit portfolio risks. In this context, an automated comprehensive quantification and/or calculation of individual risks and default correlation risks should be possible without having to use model assumptions such as, e.g. specific distributions.

According to the present invention, these objects are achieved, in particular, by the elements of the independent claims. Further advantageous embodiments are also obtained from the dependent claims and the description.

In particular, the objects are achieved by the invention in that, for the purpose of automated credit risk indexing by means of corresponding means which can comprise, for example, a computing unit, company balance data and/or stock market data are acquired and

evaluated and expected values for crediting data of individual companies are determined in automated manner, wherein predefined stock market data and/or company balance data are stored correlated with the individual companies by means of a memory module and wherein the crediting data are determined on the basis of the stock market data and/or the company balance data of a particular company by means of at least one neural network module. The at least one neural network module can comprise, for example, a neural network module with a feedforward structure, but network modules with networks of different structures such as, e.g., recurrent networks, are also possible. The neural network module can be implemented, e.g. in hardware and/or in software. As training input values of the at least one neural network module, the stock market data and/or the company balance data can be used, for example. As training output values, data based on a credit rating of the corresponding companies can be correspondingly used. As input values of the at least one neural network module, interest coverage and/or ratio of debt to total assets and/or earnings growth and/or total debt and/or market capitalization of equity and/or volatility of equity and/or ratio of debt to market capitalization of equity of the respective company can be used, for example. In particular, the crediting data can comprise, e.g. at least one credit risk index for the corresponding company. An advantage of this variant of the embodiment is, among other things, that the method for determining credit risks for a particular company and/or firm can be automated without needing empirical data. The advantage of the choice of a feedforward architecture of the neural network modules lies in their simplicity and in their time-independent way of supplying results once they have been trained.

In a variant of the embodiment, stock market data of various financial centers are automatically acquired company-individually by means of a filter module. In the same way, company balance data can also be acquired automatically company-individually from at least one corresponding memory module by means of a filter module as variant of the embodiment. The two filter modules can be implemented, e.g. individually or as common module in software and/or hardware. In one or both filter modules, a time interval can be defined, for example, which determines an expected interval between the expected values to be calculated and the company balance data and/or stock market data of the individual companies. The variant of the embodiment has the advantage, among other things, that further automation is possible. In particular, the neural network modules can be continuously updated with new data, i.e. newly trained. Similarly, developments, e.g. on the financial market, can be taken into consideration directly for the credit risk of a particular company.

In another variant of the embodiment, a user accesses a user profile, which is stored allocated to him in a user database, via a communication channel by means of a network unit and/or the user sends a crediting request to the computing unit by means of the network unit. The respective user can determine, e.g., by means of the user profiles which companies and/or financial markets and/or title categories are used for determining the crediting data. The communication channel can comprise, e.g. the international backbone network Internet and/or a mobile radio network, particularly a GSM and/or a UMTS mobile radio network and/or a WLAN. The variant of the embodiment has the advantage, among other things, that a user can trigger and/or influence the automated determination at a particular time by means of a user profile or an actual request and can access the desired data at a later time

when they are provided. In particular, this method also allows a corresponding service to be offered by means of decentralized administrative units.

In a further variant of the embodiment, crediting data and/or credit risks of individual companies are determined by means of a number of modules and/or systems according to the invention and by means of at least one additional neural network module, default correlation risks and/or at least one credit portfolio risk index is determined on the basis of the crediting data and/or credit risks of the individual companies, the input data of the at least one additional neural network module comprising output data of the modules for calculating crediting data of individual companies. The at least one additional neural network can have, e.g. a feedforward structure. The variant of the embodiment has the advantage, among other things, that default correlations of a number of individual risks are taken into consideration in the method which allows an effective determination or automated administration of credit risks and/or credit risk portfolios.

It shall be noted at this point that the present invention, apart from the methods according to the invention, also relates to a system and a computer program product for carrying out these methods.

In the text which follows, variants of the embodiments of the present invention will be described by means of examples. The examples of the embodiments are illustrated by the following attached figures:

Figure 1 shows a block diagram which diagrammatically illustrates a system for determining credit indices, wherein expected values for crediting data of individual companies 601,...,603 are calculated.

Figure 2 shows a diagram which diagrammatically shows the average industry-related default rates on the example of Germany. The diagram quantitatively shows that there is apparently a common background factor, such as the general economic situation, which leads to a uniformly aligned development trend in the default rates.

Figure 1 illustrates an architecture which can be used for implementing the invention. In this exemplary embodiment, company balance data and/or stock market data can be acquired and evaluated by means of corresponding means which comprise, e.g. a computing unit 30, wherein expected values for crediting data of individual companies and/or firms 601,...,603 are calculated. In this context, the term companies 601,...,603 is to include all possible legal and natural persons which are legally creditworthy, that is to say large, medium and small firms and companies such as simple companies, companies with limited liability, joint stock companies, holdings etc. The company balance data 3111/3121 and/or stock market data 3112/3122 can comprise, e.g. interest coverage and/or ratio of debt to total assets and/or earnings growth and/or total debt and/or market capitalization of equity and/or volatility of equity and/or ratio of debt to market capitalization of equity of the respective company. In spite of this explicit naming of possible company balance data and/or stock market data, this enumeration should not be considered in any way as restrictive for the invention but it may be appropriate, depending on the field of application and/or branch of industry, to consider and/or to lead away from the abovementioned certain data other company balance data and/or stock market data. The crediting data can comprise, e.g. at least one credit risk index for the corresponding company 601/602/603, i.e. an index which allows the credit risk (default probability

and default costs) to be determined for a company 601/602/603. Credit risk (also address risk) is generally understood to be the possible negative change in value of a financial market instrument due to an acute insolvency of the debtor (default risk) or a change in his solvency (spread risk or risk of rating change). A distinction is made between direct and conditional credit risks and settlement risks. Examples of direct credit risk are traditional credits and loans. A conditional credit risk arises from the replenishment risk in the case of derivative transactions. An example of this is that, when the option taker of an option in the trading stock defaults before exercising it, a loss occurs in the magnitude of the replenishment costs for the corresponding derivative. The settlement risk consists in not receiving a return after effected performance when performing a transaction. The crediting data can comprise both data for direct and also conditional credit risks. Determining the credit risk begins with the measurable stochastic factors which determine the probability and the magnitude of the credit risk. These relevant stochastic factors are comprised by the company balance data 3111/3121 and/or stock market data 3112/3122. The credit risk, i.e. the crediting data, includes, for example, the following risks, among others: (i) the credit event (default and change in rating). This firstly includes the default event itself (occurrence of the insolvency of the debtor. In the wider sense, credit events represent changes in the solvency of the debtor so that rating changes can also be counted as credit events); (ii) spread. Even when the rating of a debtor is unchanged, the value of financial titles threatened by default can change due to the fact that the spread demanded by the market changes; (iii) recovery rate risk. This risk is understood to be the uncertainty of the recovery rate risk when a bankruptcy event occurs (insolvency). The

recovery rate risk primarily depends on the rank of the demand and the recoverability of any securities; (iv) exposure on occurrence of the credit event. In the case of bankruptcy by the opposite party from a derivative financing transaction, losses occur in the magnitude of the replenishment costs, the magnitude of which depends on the (stochastic) development of market rates and, in the case of credit derivatives, on the development of the creditworthiness of the basic borrower. The magnitude of the loss in the case of the default is stochastic and depends on market parameters. Single credit contracts, too, exhibit a stochastic exposure since in the case of bankruptcy, the loss (the market value of the credit demands) depends on, among other things, the development of the general interest level. Using the system and/or method according to the invention for determining credit risk, the common stochastics of the above types of risk can be taken into consideration which has hitherto not been possible in this way in the prior art. For the individual credit risk, predefined stock market data 3111/3121 and/or company balance data 3112/3122 will be stored correlated with the individual companies 601,...,603 by means of a memory module 31 of a computing unit 30. For this purpose, the system can comprise, e.g., a filter module 34 for the automated company-related acquisition of stock market data 3111/3121 of various financial centers 50/51/52. In this process, the computing unit 30 can automatically access data of various financial centers 50/51/52 (e.g. New York Stock Exchange, Tokyo Stock Exchange etc.) by means of the filter module 34, e.g. via a network like the Internet, and store or update relevant data on a memory module 31, provided for this purpose, of the computing unit 30. However, the data can also be entered manually into the system or can be taken over as a whole from a third memory module. Similarly, the system can comprise a filter module 35 for the automated company-related acquisition

of company balance data 3112/3122 from at least one corresponding memory module 61. The system can also store relevant company balance data 3112/3122, correlated with the companies 601/602/603, in the memory module 31. The memory module 61 can be linked to a network unit 60, e.g. of a market research institute or a corresponding service provider or directly associated with the individual companies 601/602/603, the companies 601/602/603 providing the corresponding company balance data 3112/3122 to the computing unit 30 by means of the at least one memory module 61. A time interval can be defined, e.g., by a user 20,...,24 by means of at least one of the filter modules 34/35. The time interval determines an interval between the expected values to be calculated and the company balance data 3112/3122 and/or stock market data 3111/3121 of the individual companies 601/602/603.

The crediting data are determined by means of a neural network module on the basis of the stock market data 3111/3121 and/or the company balance data 3112/3122 of a particular company 601,...,603. The neural network module can be selected on the basis of neural networks such as, e.g. conventional static and/or dynamic neural networks such as, for example, feedforward (heteroassociative) networks like a perceptron or a multi-layer perceptron (MLP), but other network structures such as, e.g. recurrent network structures can also be implemented. The neural network module can be implemented in hardware and/or software and/or comprise corresponding components. The different network structure of the feedforward networks in contrast to networks with feedback (recurrent networks) determines the manner in which information is processed by the network. In the case of a static neural network, the structure should ensure the replication of static families of curves with sufficient quality of approximation. For the present exemplary embodiment,

multi-layer perceptrons will be selected as example. An MLP consists of a number of neuron layers having at least one input layer and one output layer. The structure is directed strictly forward and belongs to the group of feed-forward networks. Quite generally, neural networks map an m-dimensional input signal onto an n-dimensional output signal. The information to be processed is received by a layer with input neurons, the input layer, in the feedforward network considered here. The input neurons process the input signals and forward them via weighted connections, so-called synapses, to one or more hidden neuron layers, the hidden layers. From the hidden layers, the signal is also transmitted by means of weighted synapses to neurons of an output layer which, in turn, generates the output signal of the neural network. In a forward-directed, completely linked MLP, each neuron of a particular layer is connected to all neurons of the subsequent layer. The choice of number of layers and neurons (network nodes) in a particular layer must be adapted to the corresponding problem as is usual. The simplest possibility is to determine the ideal network structure empirically. It must be considered here that when the number of neurons selected is too large, the network, instead of learning, acts in a purely mapping manner whereas when the number of neurons is too small, correlations of the mapped parameters will occur. In other words, the situation is that when the number of neurons is selected to be too small, the function may not be represented. However, increasing the number of hidden neurons also increases the number of independent variables in the error function. This leads to more local minima and to the increased probability of landing in exactly one of these minima. In the special case of back propagation, this problem can be at least minimized, e.g. by means of simulated annealing. In simulated annealing, a probability is allocated to the states in the network. Analogously to the cooling of

liquid matter from which crystals are created, a large starting temperature T is selected. This is gradually reduced, the smaller the slower. In the analogy of the formation of crystals from liquid, the basic assumption is that if the matter is allowed to cool too quickly, the molecules will not arrange themselves in accordance with the lattice structure. The crystal becomes unpure and unstable at the locations affected. To prevent this, the matter will be allowed to cool so slowly that the molecules still have sufficient energy for jumping out of a local minimum. The procedure is the same in the case of neural networks. The variable T is additionally introduced in a slightly changed error function. In the ideal case, this then converges toward a global minimum.

In MLP, neural networks having an at least three-layered structure have been found to be appropriate for the application for a computer-aided system or a method for the automated credit risk indexing. This means that the networks comprise at least one input layer, one hidden layer and one output layer. Within each neuron, the three processing steps of propagation, activation and output take place. The output of the i-th neuron of the k-th layer is obtained as

$$o_i^k = f_i^k\left(\sum_j w_{i,j}^k \cdot o_{i,j}^{k-1} + b_{i,j}^k\right)$$

where, e.g. the area j = 1,2,...,N_1 applies for the run variable j for k = 2. N_1 designates the number of neurons of layer k-1. w is weight and b is bias (threshold value). Depending on application, the bias b can be selected to be identical or different for all neurons of a particular layer. The activation function

selected can be, e.g. a logarithmic sigmoidal function such as

$$f_i^k(\xi) = \frac{1}{1+e^{-\xi}}$$

The activation function (or transfer function) is used in every neuron. However, other activation functions such as tangential functions etc. are also possible according to the invention. In the case of the back propagation method, however, attention must be paid to the fact that a differentiable activation function such as, e.g. a sigmoid function, is the prerequisite for the method. i.e., e.g. binary activation functions such as, e.g.

$$f(x) := \begin{cases} 1 \text{ if } x > 0 \\ 0 \text{ if } x \le 0 \end{cases}$$

will not work for the back propagation method. In the neurons of the output layer, the outputs of the last hidden layer are summed up weighted. The activation function of the output layer can also be linear. The totality of the weightings $W_{i,j}^k$ and bias $B_{i,j}^k$ combined in the parameter or weighting matrices determine the response of the neural network structure

$$W^k = \left(w_{i,j}^k\right) \in \Re^{N \cdot N_k}$$

Thus, the following is obtained:

$$o^k = B^k + W^k \cdot \left(1 + e^{-(B^{k-1} + W^{k-1} \cdot u)}\right)^{-1}$$

The way in which the network is to map an input signal onto an output signal, i.e. the determination of the desired weights and bias of the network, is achieved by training the network by means of training patterns. The set of training patterns (index μ) consists of the input signal

$$Y^\mu = \left[y_1^\mu, y_2^\mu, \ldots, y_{N_1}^\mu\right]$$

and an output signal

$$U^\mu = \left[u_1^\mu, u_2^\mu, \ldots, u_{N_1}^\mu\right]$$

In this exemplary embodiment, the training input values of the at least one neural network module 33 or the input values during the determination of new crediting data comprise, e.g., among other things, the stock market data 3111/3121 and/or the company balance data 3112/3122. The corresponding training output values comprise, e.g. a credit rating of the companies 601/602/603. The training input values or the input values during the determination of new crediting data comprise, e.g. interest coverage and/or ratio of debt to total assets and/or earnings growth and/or total debt and/or market capitalization of equity and/or volatility of equity and/or ratio of debt to market capitalization of equity of the respective company 601/602/603. At the beginning of the learning process, the initialization of the weights of the hidden layers, that is say of the neurons in this exemplary

embodiment, can be performed, e.g. with a logarithmic sigmoidal activation function, e.g. according to Nguyen-Widrow (D. Nguyen, B. Widrow, "Improving the Learning Speed of 2-Layer Neural Networks by Choosing Initial Values of Adaptive Weights", International Joint Conference of Neural Networks, vol. 3, pp. 21-26, July 1990). If a linear activation function has been selected for the neurons of the output layer, the weights can be initialized, e.g. by means of a balanced random-number generator. For the training of the network, various learning methods of the prior art can be used such as, e.g. the back propagation method, learning vector quantization, radial basis function, Hopfield algorithm or Kohonen algorithm etc. The task of the training method consists in determining the synapses weights $w_{i,j}$ and bias $b_{i,j}$ within the weighting matrix W or the bias matrix B, respectively, in such a manner that the input patterns Y^{μ} are mapped onto the corresponding output patterns U^{μ}. To assess the learning stage, the absolute quadratic error

$$Err = \frac{1}{2}\sum_{\mu=1}^{p}\sum_{\lambda=1}^{m}(u^{\mu}_{eff,\lambda} - u^{\mu}_{nom,\lambda})^2 = \sum_{\mu=1}^{p} Err^{\mu}$$

can be used, for example. The error Err takes into consideration all patterns P_{ikf} of the training basis at which the effective output signals U^{μ}_{eff} show the nominal responses U^{μ}_{nom} predetermined in the training basis. For the present exemplary embodiment, the back propagation method shall be selected as learning method. The back propagation method is a recursive method for optimizing the weight factors $w_{i,j}$. In each learning step, an input pattern Y^{μ} is selected in accordance with the random principle and propagated through the network (forward propagation). Using the error function Err described above, the error Err^{μ} is determined for the input

pattern presented by means of the nominal response U^{μ}_{nom} predetermined in the training basis from the output signal generated by the network. The changes in the individual weights $w_{i,j}$ after the presentation of the μ-th training pattern are proportional to the negative partial derivation of the error Err^{μ} with respect to the weight $w_{i,j}$ (so-called gradient descent method)

$$\Delta w^{\mu}_{i,j} \approx \frac{\partial E^{\mu}}{\partial w_{i,j}}$$

Using the chain rule, the adaption rules known as the back propagation rule can be derived from the partial derivation for the elements of the weighting matrix in the presentation of the μ-th training pattern.

$$\Delta w^{\mu}_{i,j} \equiv s \cdot \delta^{\mu}_{i} \cdot u^{\mu}_{eff,j}$$

with

$$\delta^{\mu}_{i} = f^{\prime}(\xi^{\mu}_{i}) \cdot (u^{\mu}_{nom,i} - u^{\mu}_{eff,i})$$

for the output layer or

$$\delta^{\mu}_{i} = f^{\prime}(\xi^{\mu}_{i}) \cdot \sum_{k}^{K} \delta^{\mu}_{k} w_{k,i}$$

for the hidden layers. The error is propagated through the network in the reverse direction, beginning with the output layer (back propagation) and distributed over the individual neurons in accordance with the originator principle, as it were. The proportionality

factor s is called the learning factor. During the training phase, a neural network is presented with a limited number of training patterns which sufficiently accurately characterize the mapping to be learnt. In the present exemplary embodiment for determining the crediting data, the training patterns can comprise all known stock market data 3111/3121 and/or company balance data 3112/3122. However, a user-definable selection of data (e.g. according to the industrial field of the party receiving credit) e.g. from the stock market data 3111/3121 and/or company balance data 3112/3122 is also conceivable. If the network is subsequently presented with an input signal which does not precisely correspond to the patterns of the training basis, the network interpolates or extrapolates between the training patterns, within the framework of the mapping function learnt. This property is called the generalization capability of the networks. It is characteristic of neural networks that neural networks have good error tolerance. This is a further advantage compared with the systems of the prior art. Since neural networks map a multiplicity of (partially redundant) input signals to the desired output signal(s), the networks are found to be resistant to a failure of individual input signals and with respect to signal noises, respectively. A further interesting characteristic of neural networks is their learning capability. In principle, it is possible therefore to allow a system, once trained, to permanently/periodically relearn or adapt during operation which is also an advantage compared with the systems of the prior art. Naturally, other methods can also be used for the learning method such as, e.g. a method according to Levenberg-Marquardt (D. Marquardt, "An Algorithm for least square estimation of non-linear Parameters", J. Soc.Ind.Appl.Math, pp. 431-441, 1963 and M.T. Hagan, M.B. Menjaj, "Training Feedforward Networks with the Marquardt Algorithm", IEEE

Transactions on Neural Networks, Vol. 5, No. 6, pp. 989-993, November 1994). The Levenberg-Marquardt method is a combination of the gradient method and of the Newton method and has the advantage that it converges more rapidly than the abovementioned back propagation method but needs a greater storage capacity during the training phase.

Once the training phase of the at least one neural network module 33 is ended, crediting data can be determined by means of the system in that the input values comprise the stock market data 3111/3121 and/or the company balance data 3112/3122 of the corresponding companies 601,...,603. Like the training input values, these input values can comprise, e.g. interest coverage and/or ratio of debt to total assets and/or earnings growth and/or total debt and/or market capitalization of equity and/or volatility of equity and/or ratio of debt to market capitalization of equity of the respective company 601/602/603. Furthermore, the system can comprise, e.g. one or more network units 10/11/12/14/15 by means of which a user 20,...,24 can access user profiles 3220,...,3224 allocated to him and stored in a user database 32 via a communication channel 40/41 and/or send a crediting request to the computing unit 30. Communication via the communication channel 40/41 takes place, for example, by means of special short messages, e.g. SMS (short message services), USSD (unstructured supplementary services data) messages or other techniques such as MExE (mobile execution environment), GPRS (generalized packet radio service), HSCSD (high speed circuit switched data) data services, WAP (wireless application protocol) or UMTS (universal mobile telecommunication system) or via an information channel. The communication channel 40/41 comprises, for example, a mobile radio network such as a terrestrial mobile radio network, e.g. a GSM or UMTS network or a satellite-based mobile radio network

and/or one or more fixed networks, for example the public switched telephone network (PSTN), the worldwide Internet or a suitable LAN (local area network) or WAN (wide area network). The data exchange between the network unit 10/11/12/14/15 and the computing unit 30 takes place, e.g. via a corresponding interface implemented in software and/or hardware. The network unit 10/11/12/14/15 can be, e.g. a personal computer (PC), a PDA, a laptop or a mobile radio device and can be unambiguously identified, e.g. on the basis of an identification module of the network unit 10/11/12/14/15, by a conditional access server, e.g. by means of the directory number (MSISDN: mobile subscriber ISDN or, respectively, IMSI: international mobile subscriber identification). The identification module can be a fixed component of the network unit 10/11/12/14/15, e.g. as is normal usage in mobile radio devices in the United States or a removable chip card, as is more usual in Europe, such as, e.g. a SIM (subscriber identification module) card, WIM (WAP identity module) card or a UIM (UMTS identity module) or smart card. The chip card has, e.g. credit card format ISO 7816 or plug-in format. The directory number can be associated with the identification module, e.g. via a HLR (home location register) in that the IMSI (international mobile subscriber identification) is stored in the HLR correlated with a directory number, e.g. a MSISDN (mobile subscriber ISDN). However, the identification can also take place, e.g. by inputting a PIN (personal identity number) or via a biometric ID etc. By means of the user profiles 3220,...,3224, it can be definable, e.g. for the respective user 20,...,24, which companies 601,...,603 and/or financial markets 50/51/52 and/or title categories are to be taken into consideration for determining the crediting data. The communication channel 40/41 can comprise, e.g. the international backbone network Internet. However, the communication

channel 40/41 can also comprise, e.g. a mobile radio network, particularly a GSM and/or a UMTS mobile radio network and/or a WLAN. In the user profiles 3220,...,3224 or in a crediting request, respectively, a user 20,...,24 can specify, e.g. from which companies 601,..,603 he wishes to have the credit risk determined. In particular, he can also specify a credit risk portfolio for which the credit risk is to be determined. According to the invention, it is not only the individual risks which are taken into consideration for the credit portfolio but also the risk correlations as will be shown below. Using the user profile 3220,...,3224, a user can also determine, e.g. an automated monitoring of an individual credit and/or a credit portfolio. The results are sent either directly to the corresponding network unit 10,...,14 by the computing unit 30 and/or stored accessible for the user 20,...,24 on a data memory of the central processing unit 30. Finally, it must be mentioned that, e.g. accounting data can also be transmitted at least partially periodically during and/or after the access of the computing unit 30 to a transaction server which handles the further charging for costs or, respectively, the performance received by the user 20,...,24. It is also possible to store an amount of money in a data memory of the network unit 10,...,14 such as, e.g. a chip card and to debit the costs on the basis of cost data which comprise the cost amounts for the access of data of the computing unit 30 per specified accounting unit. This makes it possible to offer the method and system as a service to third parties within a network.

For the variants of the embodiment for determining risk parameters of a credit portfolio it is of importance to point out that the risk of a credit portfolio is not identical with the sum of the individual risks. To determine the credit risk, particularly the credit risk

within a credit portfolio, the system or the method must take into consideration the common stochastics of all risks. It is only this which allows a real quantification of the total risk of a portfolio and thus an automated management of the portfolio. This means that all correlations between the individual risks must also be taken into consideration. Correlation or default correlation is understood to be the probability of a default, for example of two debtors, wherein this common default probability is not equal to the probability of an individual default. Similarly, the system should be able to detect correctly the relationship between the recovery rates of two parties receiving credit. The system must detect both the number of defaults and the magnitude of the resultant losses. It may be appropriate for the system to also take into consideration correlations of recovery rates. It is also of importance that the system detects correlations between recovery rates and default probabilities. The case of building finance can be quoted as an example in this case. Generally, the recovery rate significantly depends on the level of land and real property prices which, in turn, is an important determinant of the insolvency rate of real property credits. If financial instruments with credit risk act as security (e.g. corporate bonds), the recovery rate is dependent on the value of the loan and thus on the development of the probability of bankruptcy. The credit risk systems known in the prior art have the disadvantage, however, that they are mostly far from being capable of detecting portfolio effects on a such detailed level. For obvious reasons (availability of data and the complexity of the problems involved must be mentioned essentially), the methods of the prior art restrict their analysis of correlation effects in the credit risk field to taking into consideration stochastic dependencies within the group of credit events. In this context, only the

correlation analysis of defaults is taken into consideration in most cases. Stochastic dependencies in the field of recovery rate risks or of credit exposure can be considered either not at all or only via greatly simplifying ad hoc assumptions (e.g. independency assumptions). In the case of the correlations, it is known that the greatest influence on a credit portfolio risk is the default correlation or the probability of a simultaneous default of a number of debtors. An example of this is the insolvency time series for Germany (figure 2; Federal German Office For Statistics), where it can be quantitatively seen that the default rates are obviously not independent of one another in various branches. There is clearly a common background factor such as the "general economic situation". This leads to a uniformly aligned development of the default rates in the course of time. It follows from this that default events cannot be events which are stochastically independent of one another. The reference numbers in figure 2 show insolvency series for the aggregate 71, banks and insurances 72, energy and mining 73, telecommunication and transport 74, services 75, agriculture 76, building construction 77, processing industry 78 and trade 79. In a variant of the embodiment according to the invention with an additional neural network, the abovementioned correlations can also be taken into consideration without assuming models. To this end, the system and/or method for the automated determination of credit portfolio risks comprises a number of modules and/or systems for calculating crediting data and/or credit risks of individual companies 601,...,603. As stated above, the modules and/or systems for calculating crediting data and/or credit risks can be implemented in hardware and/or software. This variant of the embodiment comprises at least one additional neural network for determining a credit portfolio risk and/or default correlation risk on the basis of the crediting

data and/or credit risks of individual companies 601,...,603. The at least one additional neural network can also have, e.g. a feedforward structure but other structures are also conceivable. The input data of the at least one additional neural network comprise the output data of the individual modules and/or systems for calculating individual credit risks of the companies 601,...,603. Apart from the output data of the modules for calculating the individual risks, the input data of the additional neural network can also comprise further data such as e.g. stock market data and/or economical data. To train the additional network, it is possible to use, e.g. available data for default risks and/or default correlations of earlier years. Using this variant of the embodiment, it is thus possible to correctly determine credit portfolio risks without having to use model assumptions, e.g. via the default correlations of the companies 601,...,603. Since, in particular, no empirical estimations are necessary in the variant of the embodiment, the system and method according to the invention also allows an automated monitoring and management of credit risk portfolios which has not been possible in this way by means of the methods of the prior art.